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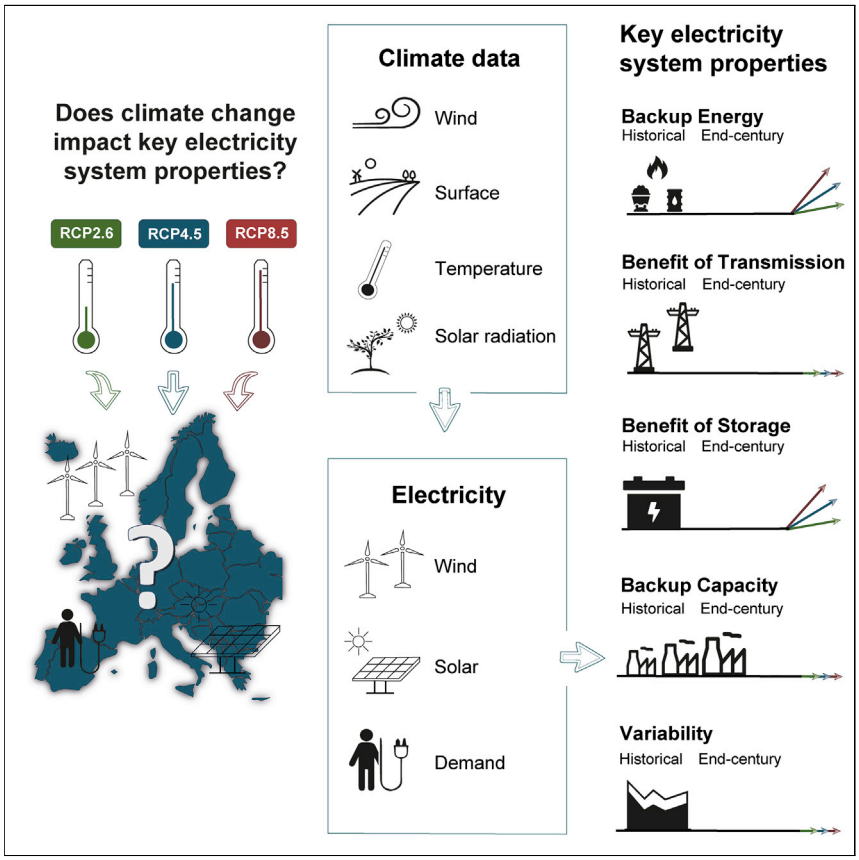
21st Century Climate Change Impacts on Key Properties of a Large-Scale Renewable-Based Electricity System



Wind and solar sources currently drive an increased weather-dependent electricity production because of decreasing costs and efforts to mitigate climate change. Unfortunately, some degree of climate change appears to be unavoidable. We use different projections of climatic outcomes over the 21st century to assess how important key metrics of a highly renewable electricity system are affected by climate change.

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HIGHLIGHTS

Climate change shows impacts on large-scale metrics of a European electricity system

Largest climate impacts are observed within fully wind-dominated electricity systems

6 high-resolution CMIP5 GCMs under the forcing of three IPCC RCPs have been used

State-of-the-art wind and solar capacity factors and electricity demand data were used

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21st Century Climate Change Impacts on Key Properties of a Large-Scale Renewable-Based Electricity System

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SUMMARY

Falling prices and significant technology developments currently drive an increased weather-dependent electricity production from renewables. In light of the changing climate, it is relevant to investigate to what extent climate change directly impacts future highly weather-dependent electricity systems. Here, we use three IPCC CO_2 concentration pathways for the period 2006–2100 with six high-resolution climate experiments for the European domain. Climate data are used to calculate bias-adjusted 3-hourly time series of wind and solar generation and temperature-corrected demand time series for 30 European countries using a state-of-the-art methodology. Weather-driven electricity system analysis is then applied to compare five key metrics of highly renewable electricity systems. We find that climate change changes the need for dispatchable electricity by up to 20%. The remaining key metrics, such as the benefit of transmission and storage as well as requirements for balancing capacity and reserves, change by up to 5%.

INTRODUCTION

The global climate is currently undergoing vast changes, primarily due to anthropogenic emissions of heat-trapping gases into the atmosphere.[1] As a consequence, the global average surface temperature has increased since the 1960s by approximately 0.2° C per decade. A similar rate of temperature increase is projected to occur during the first half of the 21st century[2] and, at present, the changing climate is showing global impacts on natural and human systems. In this work, we focus on the impacts of a changing climate on the dynamics of a future, highly renewable, large-scale electricity system for Europe.

Research on the impacts of climate change on large-scale electricity systems is in its infancy, and few studies have been performed in this field.[3] For an aggregated European energy system, Dowling[4] finds outweighing demand-side impacts to the supply side, based on the Prospective Outlook for the Long-term Energy System model (POLES). Because of global heating, the cooling demand increases while the heating demand decreases.[4] More specifically, a study conducted by Pilli-Sihvola et al.[5] shows a decreasing need for heating in central and northern Europe based on the SRES A2, A1B, and B1 emission scenarios. Southern Europe experiences a large increase in cooling demand, which in turn overcomes the decrease in heating demand.[5] This finding is in agreement with a study on Germany and Austria for the last quarter of the 21st century.[6] The spatial distribution of the heating and cooling needs are further reflected in increasing needs for electricity in southern Europe and decreasing needs in northern Europe.[7] Individual country studies on

Context & Scale

Globally, electricity production from wind and solar sources is increasing significantly. The increase is primarily driven by lower costs and by political efforts to mitigate climate change. Climate change, however, may radically change the weather that drives these sources of renewable energy. We find that the impact of climate change on a future highly renewable European electricity system is up to 20% for a few key metrics when compared to corresponding numbers for a historical climate scenario. In most cases, however, the relative impact is an order of magnitude smaller. The level of impact is, in general, smaller than corresponding differences from one weather year to another and also compared to differences between system designs, e.g., with different levels of international power transmission lines or different mixes of wind and solar generators.

Norway,[8] Finland,[9] Slovenia,[10] Austria,[11] and Switzerland[12] agree upon the latter findings. Spinoni et al.[13] show that the heating degree days decrease significantly, especially over Scandinavia and European Russia when using the representative concentration pathway scenarios (RCP) 4.5 and RCP8.5. For identical projections, the cooling degree days are increasing, especially over the Balkans and the Mediterranean region.

By using the SRES A1B emission scenario, Tobin et al.[14] and Barstad et al.[15] find negligible changes in the wind power potential over the Baltic Sea and the surroundings. Similar results are found by Tobin et al.[16] for Europe by using the RCP4.5 and RCP8.5 emission scenarios. McColl et al.[17] arrive at similar conclusions for the UK, Seljom et al.[8] for a case study on Norway based on 10 climate experiments, and Koch et al.[18] for Germany by using the RCP2.6 and RCP8.5 emission scenarios for the period 2031–2060. Moreover, Schlott et al.[19] discover increasing wind correlation lengths along with increasing wind power generation in the same regions of Europe by using the RCP8.5 emission scenario. Tobin et al.[14] and Bloom et al.[20] project a decreasing wind power potential over the Mediterranean area by using the SRES A1B and A2 emission scenarios. Similar findings along with decreasing correlation lengths are shown by Schlott et al.[19] For an aggregated EU27, Dowling[4] found a slight increase in the wind power production until mid-century, based on the SRES A1B and E1 emission scenarios. For a wind-dominated European energy system under the impact of the RCP8.5 emission scenario, increasing needs for conventional power and storage are found in most of the central, north, and northwest areas,[21] with a more homogeneous wind power generation[22] at the end of the 21st century. Jerez et al.[23] project a decreasing solar power generation in the Scandinavian area and slight increases over southern Europe by using the RCP4.5 and RCP8.5 emission scenarios. This corresponds with increased means of solar irradiation along with increased solar correlation length in large parts of southern Europe.[19] The opposite behavior is observed for the northern parts of Europe.[19] For an aggregated EU27, an increasing amount of solar photovoltaic (PV) generation is found.[4] Based on 44 electricity scenarios for Europe, Berrill et al.[24] find that large penetrations of wind and solar power emit the least CO_2 within the ensemble of scenarios and, as a consequence, contribute the most to climate change mitigations.

We add to the literature by investigating the key infrastructure metrics of a fully connected, highly renewable European electricity system by using the latest generation of climate projections provided by the Intergovernmental Panel on Climate Change (IPCC).[25] The climate data used in this study originate from six combinations of four RCMs (regional climate models), downscaling three CMIP (coupled model intercomparison project) phase 5[26] GCMs (global climate models) under the forcing of IPCC RCPs. This study utilizes only a subset of the GCMs that are available in the ensemble of CMIP5 GCMs. Former studies[27,28] evaluate the climate model performance of capturing, e.g., storm track densities, temperatures, or precipitations, by using a large ensemble of GCMs and show acceptable agreements among a majority of the GCMs, including the ones adapted in this work.

In order to represent a broad range of climate outcomes, three scenarios, RCP2.6,[29] RCP4.5,[30] and RCP8.5,[31] have been implemented into the global climate models. RCP2.6 is a climate projection that provides the necessary steps consistent with the goals of the 2015 Paris agreement, which aims at keeping long-term global temperature increases below 2°C. In particular, there is an urgent need for both short- and long-term action in reducing the CO_2 emissions, as explained in detail in the Emission Gap Report 2017.[32] RCP4.5 is highly influenced by high CO_2 emission

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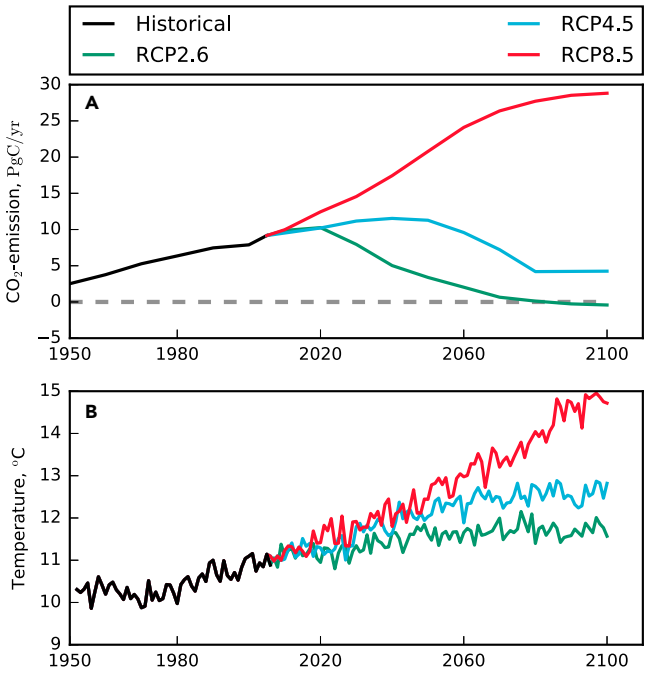

Figure 1. RCP Key Metrics

(A) CO_2 emissions as a function of model year for the various projections of climate outcomes.
(B) Average near-surface temperature over Europe for the regional climate model HIRHAM5-EC-EARTH as a function of model year for identical pathways. Black, green, blue, and red projections represent the historical, RCP2.6, RCP4.5, and RCP8.5 pathways, respectively.

cost policies, while RCP8.5 has no climate policies implemented. The underlying assumptions of the pathways result in CO_2 emissions as shown in Figure 1A. RCP2.6 and RCP4.5 show decreasing projections of the CO_2 emissions during the 21st century, while RCP8.5 leads to an increased projection that stagnates at the end of the century. For further information on the pathways, refer to the Supplemental Information Section 1.4. These projections are reflected in the European average temperature, e.g., the RCM HIRHAM5,[33] downscaling the global climate model ICHEC-EC-EARTH,[34] from now on denoted as HIRHAM5-EC-EARTH, shown in Figure 1B. Based on the emission scenarios, 3-hourly data on climate variables with a 0.11° × 0.11° spatial resolution have been fostered on behalf of the EURO-CORDEX project.[35,36] These data are used to calculate the time series of wind and solar power generation as well as climate-corrected electricity demand time series from which the final results are derived. Figures 2B–2D exemplify the 2080–2100 model time span average near-surface temperature over Europe for the future emissions scenarios based on the climate model HIRHAM5-EC-EARTH. Figure 2A represents the absolute temperature of the historical period 1986–2006. The most extreme temperature increases reach values of greater than 6°C.

In the present study, the main source of error originates from the performance of the GCMs that provide the boundary conditions for the RCMs.[37] It is also known that biases might occur during the downscaling from GCM to RCM because of a change in the temporal resolution, as discussed by Cannon et al.[38] Various studies have engaged in tracking the evolution of CMIP5 GCMs and their predecessor CMIP3 GCMs by comparison to observed data, satellite data, or reanalysis. In Supplemental Information Section 1.2, we detail the biases in the wind speed, temperature, global radiation budget, and cloud cover projections as these are crucial for our study.

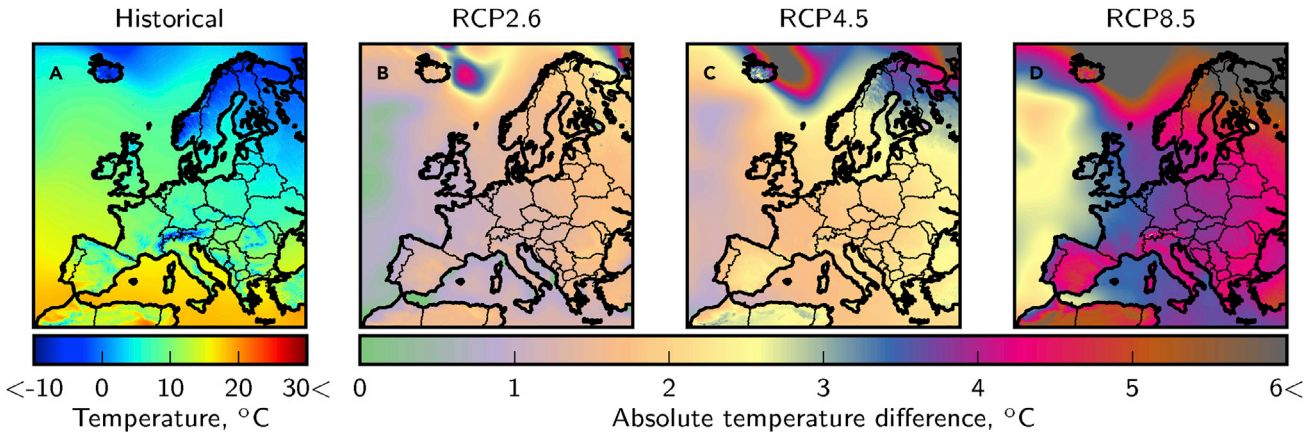

Figure 2. 20-Year Average Values of the Near-Surface Temperature

The 2 meter surface temperature is based on the latest generation of IPCCs climate projections, RCPs, for the climate model HIRHAM5-EC-EARTH. (A) Average absolute temperature for a historical period ranging from 1986 to 2006 along with a unique color bar.

(B–D) Temperature increase at the end of the century during 2080–2100 according to scenarios (B) RCP2.6, (C) RCP4.5, and (D) RCP8.5 relative to the historical period, sharing one color bar.

Although improvements are evident in the prediction of climate variables, there is still a need for more attention in this field. A detailed description of biases within the RCMs is omitted as the GCM errors propagate through the downscaling. However, the errors introduced in the downscaling should not be neglected.

In this work, the combined errors from GCMs and RCMs are partially taken into account by evaluating the results on data from six different combinations of GCM and RCM models. Relatively small deviations are observed between these independent datasets, which leads to the conclusion that model-specific biases are not a major source of error. However, we cannot exclude biases that are similar for all model combinations.

RESULTS AND DISCUSSION

End-of-Century Climate Impacts

Initially, we present results based only on the climate model HIRHAM5-EC-EARTH. Toward the end, we present the robustness of the results by comparing similar findings from all six climate models. We stress, however, that in the analysis all six climate models have been treated identically.

Except for a few cases, the different climate scenarios show a limited impact on the five key metrics of a highly renewable European electricity system. This is illustrated in Figure 3, where the key metrics are shown as a function of the wind-solar mix for the end of the century period 2080–2100, where all RCPs are most developed. We observe that the difference between average values for different climate scenarios is smaller than the corresponding annual variation (one sigma) in nearly all cases. In other words, annual variations within a given climate change scenario are larger than the difference between scenarios. This indicates that it is more important to incorporate existing inter-annual variation in long-term electricity system design decisions, as discussed by Collins et al.,[54] compared to including the effect of climate change. Furthermore, a paired t test reveals that, in most cases, the null hypothesis of no difference between the historical and the future 20-year mean values of the key metrics cannot be rejected (95% confidence). To some extent, this finding is related to the choice of generator capacities relative to demand because a decrease in

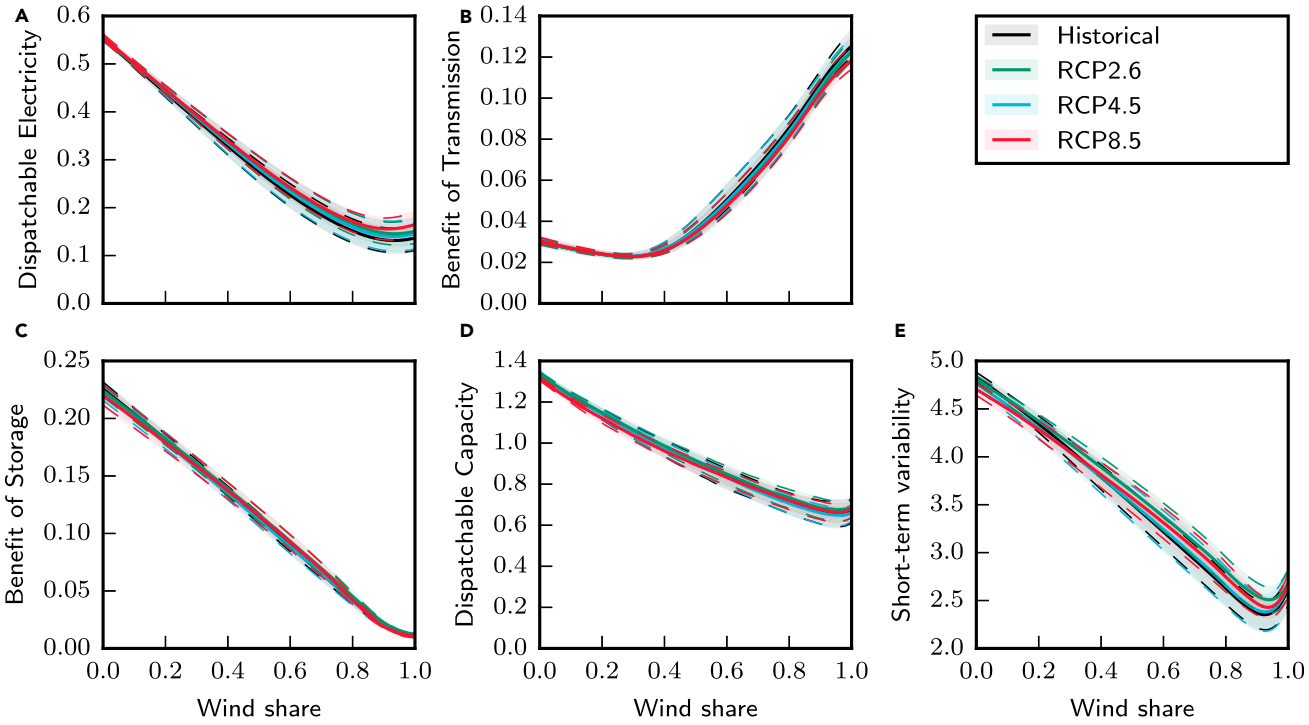

Figure 3. Key Metrics as a Function of the Wind-Solar Mix for the Historical and End-of-Century Periods

The historical period covers 1996–2006 (black), and end-of-century period covers 2080–2100 for the RCP2.6 (green), RCP4.5 (blue), and RCP8.5 (red) pathways. A wind-solar mix equal to zero represents a solar-only electricity system, and a wind-solar mix of one represents a wind-only electricity system. The averages of the annual values are indicated with fully drawn lines, and the corresponding ranges (one sigma) are shown with dashed lines. All key metrics are unitless, as described in the Experimental Procedures. (A) Dispatchable Electricity, (B) Benefit of Transmission, (C) Benefit of Storage, (D) Dispatchable Capacity, (E) Short-term variability.

demand happens to be balanced by an independent decrease in consumption. This is evident from Table 1, where it can be seen that both annual demand and wind and solar generation are decreasing slightly in the future scenarios. Furthermore, a t test shows that, at a 95% significance level, the annual demand and annual solar capacity factors can both be considered different for the different climate change scenarios in nearly all cases. Test results for the wind capacity factors, on the other hand, are inconclusive. The magnitude of the effect of climate change on electricity demand is similar to the impact on the supply side. However, the inter-annual variability of the demand is smaller by about an order of magnitude, as can be seen in Table 1. The limited demand-side impact is primarily explained by the relatively low level of electrified heating and cooling in Europe. Should a larger share of the heating demand be electrified in the future, as suggested by several studies,[55–57] then the effect of climate change on the demand side would increase accordingly.[7,58] All test scores, mentioned above, are listed in the Supplemental Information Section 6.

The estimates of the difference between the climate change scenarios can also be compared to the difference between systems with different wind-solar mixes within a scenario. This comparison reveals to what extent it is more important to choose the right wind-solar mix independently of RCPs or whether it is most important to design the electricity system for the right RCP.

For the dispatchable electricity key metric, shown in Figure 3A, we find the largest difference between climate scenarios for a wind-solar mix of 1.0. The RCP8.5 scenario has an average value of 0.17, while the corresponding number for the historical

Table 1. 20-Year Average Values of the Normalized Wind $\langle W \rangle_{20yr}$ and Solar $\langle S \rangle_{20yr}$ Power and Electricity Consumption $\langle L \rangle_{20yr}$ for the European Domain

	Historical	RCP2.6	RCP4.5	RCP8.5
$\langle W \rangle_{20yr}$	1.00 ± 0.03	0.98 ± 0.02	0.99 ± 0.04	0.96 ± 0.03
$\langle S \rangle_{20yr}$	1.00 ± 0.01	0.99 ± 0.02	0.98 ± 0.02	0.97 ± 0.03
$\langle L \rangle_{20yr}$	1.000 ± 0.005	0.995 ± 0.003	0.992 ± 0.005	0.986 ± 0.003

One sigma standard deviations are shown after each value. All values have been normalized to the corresponding values calculated for the historical period.

period is 0.14, i.e., a difference of 0.03. The minimum dispatchable electricity is achieved for a wind-solar mix of about 90%. If the system is designed without storage, minimum surplus variable renewable electricity (VRE) occurs at the same mix, but if long-term storage is included, Heide et al.[48] showed that the minimum of surplus moves to a wind-solar mix of about 60%. From Figure 3A, we see a corresponding change in the average dispatchable electricity of approximately 0.1 for all climate scenarios.

For each of the key metrics, the absolute value at a given wind-solar mix as well as, e.g., the location of minimum and maximum values, can be compared to the difference between climate scenarios.

For all climate scenarios, the dispatchable electricity peaks for a solar-dominated system at slightly more than half the electricity consumption. This is explained by the day-night pattern in which little dispatchable electricity is needed during the daytime and full dispatchable electricity is needed for the nighttime. On the other hand, the production of wind power during both day- and nighttime reduces the need for dispatchable electricity to about 15% of the annual demand. These findings are in agreement with earlier work based on historical data.[48] As stated above, the largest difference between climate scenarios occurs for wind-dominated systems, where the absolute value is also lowest. In this case, the dispatchable electricity may change by up to 20% as an effect of climate change. Such a change may have a significant impact on decisions depending on, e.g., fuel needs and levelized cost of electricity from both dispatchable sources and VREs.

The benefits of transmission (Figure 3B) and short-term storage (Figure 3C) exhibit opposite behaviors in the sense that the former grows with an increasing wind-solar mix and the latter declines. This is because both are highly dependent on the coupled spatial and temporal correlation lengths of the wind speeds and solar irradiance.[59] The high correlation lengths of the solar irradiance due to the systematic variability of the sun's position in the sky give rise to low transmission benefits and high short-term storage benefits. Because of the simultaneous production of PV power over large areas, minor needs for transmission are present for a dominant solar share, whereas the day-night cycle allows storage to cycle relatively often.[60] For a large wind share, on the other hand, the smaller wind-speed correlation length of approximately 600–1,000 km and the related synoptic timescale of about 1 week lead to increasing transmission benefits and lower short-term storage utilization. In both cases, the largest absolute difference between climate scenarios occurs where each of the metrics peak. As a result, the impact of climate change is limited to less than 5% here. This means that for a large-scale electricity system, major design decisions related to international transmission and storage are not strongly affected by climate change. At a finer spatial resolution, some changes in the spatio-temporal correlations are expected.[21,22]

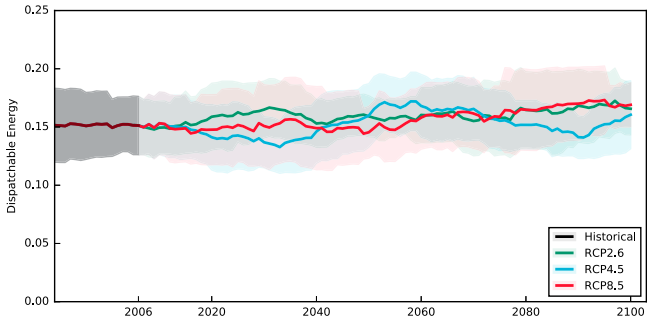

Figure 4. Evolution of the Dispatchable Electricity as a Function of Model Year for the Climate Model HIRHAM5-EC-EARTH

The historical period covers 1996–2006 (black), and the future scenarios RCP2.6 (green), RCP4.5 (blue), and RCP8.5 (red) cover the years 2006–2100. The wind-solar mix is 0.8. The 20-year averages of the annual values are indicated with fully drawn lines, and the corresponding ranges of the one-sigma standard deviation are shown with shaded areas.

The short-term variability (Figure 3E) shows higher values for low solar shares. This behavior is due to stronger intra-day temporal variations in the solar irradiance compared to temporal variations in the wind speeds. This is further reflected in the dispatchable capacity (Figure 3D). In both cases, the maximum differences between climate scenarios are all limited to less than 3% of the corresponding absolute value. The dispatchable capacity describes the maximum power required to offset calms in weather-based generation, and the short-term variability is a proxy for the reserves required on standby to compensate intra-day weather variations. Climate change is often said to result in more erratic weather,[61] but the key metrics show that for large-scale electricity networks, the size for both long-term and short-term reserves remains largely unchanged. This is likely due to the fact that extreme situations also occur in the 20-year historical period, albeit not as often.

Climate Impacts during the Century

A number of studies focus on the end of the century period alone. However, we also explore the evolution of the key metrics throughout the century. In the following, we focus on the dispatchable electricity for a wind-solar mix of 0.8, shown in Figure 4. Similar results can be found for the other key metrics in the Supplemental Information Section 6. For this case, we do not find a gradual transition from the historical reference period toward the end of the century. Instead, the trajectories of the RCPs change over time such that, e.g., the 20-year average values of each RCP cross the other trajectories multiple times. This means that the general conclusions about the relative importance of climate change on the electricity system, drawn above for the end of the century period, also hold for the transition, and it is not possible to regard specific numerical differences between RCPs as the product of a gradual evolution toward a stable climatic endpoint. Rather, the 20-year averages are not stable to an extent where they can be regarded as different between RCPs. A longer time window could be used instead. However, since the climate is changing over the course of the century (see Figure 1), long periods do not represent a stable climatic situation.

Ensemble of Climate Models

Above, we have discussed results based on the HIRHAM5-EC-EARTH climate model. Now, we turn to the five other combinations of regional and global climate models included in the study in order to establish to what extent the results are in agreement across the models. In general, we do not find identical numerical results

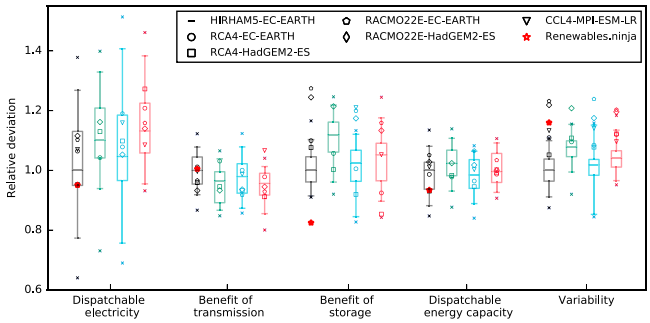

Figure 5. Key Metrics for Six Regional Climate Models from the EURO-CORDEX Project

These are compared for the historical period 1986–2006 (black) and end-of-century 2080–2100 for the RCP2.6 (green), RCP4.5 (blue), and RCP8.5 (red) scenarios. Annual values for the HIRHAM5-EC-EARTH model are indicated as boxplots. The 5% and 95% quantiles of each key metric are marked with an "x." For the remaining models, only the median values of the annual means are shown. The red star shows the key metrics for the Renewables.ninja reanalysis time series. All key metrics are normalized to the median of the respective metric in the historical period of the HIRHAM5-EC-EARTH model.

for all models despite the fact that all time series have been bias adjusted on the same historical period against the same reference. However, the overall findings remain, independently of the models. Figure 5 shows a comparison of the five electricity system key metrics for the different models in the historical period as well as in the end-of-century period for the RCPs. In most cases, the 20-year average values fall between the first and the third quartile of the annual variation, which means that the difference between individual RCMs is smaller than the annual difference within a given RCM. For the variability, this is not the case. The main reason for this is that the wind and solar time series are bias adjusted such that the distribution of instantaneous values matches the reference. However, the variability depends on the correlation between consecutive hours. This difference is not directly subject to correction, which means that models are likely to behave more differently on this parameter. Identical key metrics are also shown for the reanalysis Renewables.ninja[45,46] time series as a red star. Here, we observe a conclusion similar to that of the climate models. This reflects the adequacy of bias-corrected climate data in terms of use for power system analysis.

Conclusion

The different climate change scenarios show a modest impact on the key metrics that are representing the gross properties of a highly renewable European electricity system. On the supply side, both wind and solar power generation are affected in a way that generally reduces performance slightly as their average electricity output decreases and their variability increases with an increasing effect of climate change. Consequently, the most extreme impacts of climate change are observed within fully wind-dominated electricity systems. In this regime, the dispatchable electricity changes up to 20% of the historical values. Changes in the benefit of transmission and benefit of storage stay below 5% of historical values. Changes in the short-term variability stay below 3%.

An important consequence of these findings is that for most of the key metrics that are studied in this work, it is not required to take into account the effect of climate change on the VREs wind and solar when designing gross properties of future highly renewable electricity systems. However, other properties, e.g., siting of renewable

generators and selection of conventional generators, are not studied in this work, and the impact of climate change remains inconclusive. The need for dispatchable electricity is influenced by climate change, in some cases, depending on the VRE composition in the electricity system.

In designing a future highly renewable electricity system that is robust against climate change, it is most important to focus on reaching a mixture of wind and solar power generation that minimizes the need for dispatchable electricity as the effect of climate change simulated by typical GCMs has a modest impact on the gross design properties of future highly renewable electricity systems. This suggests that, to first order, the gross character of highly renewable power system design solutions is not strongly affected by differences in climate produced by the current generation of GCMs under different IPCC RCP scenarios. Further investigations, however, are required to understand the quality of GCM representation of climate change in key meteorological properties and their impact on power system design in more sophisticated modeling frameworks.

This modeling approach is easily adaptable to model large-scale features of highly renewable electricity systems in other parts of the world. Should a stronger sector coupling, in particular between the heating, cooling, and electricity sectors, become a reality, the demand-side impact of climate change would increase beyond what has been discussed in this study.

EXPERIMENTAL PROCEDURES

This section describes the electricity system modeling approach, data conversion and calibration procedures, and the electricity system key metrics. For a formal definition of these quantities, see Supplemental Information Sections 2.1–2.3.

Weather-Driven Electricity System Modeling

Weather-driven electricity system modeling was introduced for the first time by Heide et al.[39] It is a type of top-down analysis that is particularly useful for isolating and understanding the impact of weather dynamics on an electricity system with a large penetration of variable sources, e.g., wind and solar. In addition to Europe, this type of modeling approach has previously been applied to model large-scale electricity systems in the US[40] and China.[41] But unlike most technology-rich bottom-up models, it is not well suited for determining, for example, the fuel mix of conventional dispatchable production units or to include political aspects of energy system design decisions. Further restrictions of identifying cost-optimized solutions or planning technology-based taxes, subsidies, or standards would emerge consequently. However, before addressing these issues, it is important to quantify how impactful climate change is on the important electricity system key metrics since changes in these will also change the boundary conditions for more detailed design problems. In this way, differences in key metrics for different future climate scenarios indicate that more than one end-point solution must be considered when planning the pathway from the present-day electricity system to a highly renewable system, as studied here. Similarity between the key metrics, on the other hand, indicates that the end-point solution is likely to be independent of the climate outcome. In this paper, we implement a simplified large-scale European electricity system, of which the supply side consists solely of wind and solar power generation as well as a generic dispatchable power source, e.g., dammed hydro power or gas turbines. The demand side consists of national electricity demand. This type of electricity system aggregates the country-wise wind and solar power

generation profiles into system-wise profiles. The same applies for the electricity consumption profiles. The effect of power transmission in this system was introduced by Rodriguez et al.[42,43]

The effect of climate change enters the modeling via the weather-dependent wind and solar generation time series as well as the temperature-dependent part of the electricity demand. State-of-the-art methodology has been used to convert raw wind and solar climate data into 3-hourly country-wise wind and solar capacity factor time series. For the wind capacity factors, an optimized Gaussian convolution is applied to the original wind power curve in the conversion process.[44] This has been shown to compensate well for the limited spatial and temporal resolution of the climate model data.[44] The solar conversion includes solar position geometry, calculation of direct, diffuse, and reflected irradiance on a tilted surface, a model for the photovoltaic panels that include temperature-dependent efficiency and inverter losses. In this case, an optimized Weibull curve is used to correct the model output. In both cases, the free model parameters are determined individually for each country and each climate model such that the relative entropy between the time series and an already bias-corrected reference, provided by Renewables.ninja,[45,46] is minimized for the historical period 1986–2006; see Supplemental Information Section 3. Hourly country-wise electricity consumption profiles have been provided by the European Network of Transmission System Operators for Electricity (ENTSO-e).[47] These have been corrected for effects of heating and cooling by using the degree-day method; see Supplemental Information Section 4.

In the work presented here, wind and solar generator capacities have been scaled such that the EU-wide average generation over the historical period matches the average demand for electricity. This choice has previously been shown to describe the dynamics of a highly renewable electricity system well.[39] Because of the state of fluctuating weather events and electricity consumption behavior, the generation and load profiles differ in most time steps. This difference is referred to as the generation-load mismatch, which is defined formally in Supplemental Information Section 2.1. For high renewable penetrations, the generation-load mismatch means that a surplus of the VRE will sometimes be available. This surplus may be either transported to other locations, used by new flexible consumption, stored for later use, or simply curtailed. At other times, VRE generation is lacking, and an ancillary system must balance the difference between supply and demand, e.g., by a combination of conventional power plants, dispatchable renewable electricity such as dammed hydropower, and electricity storage systems. Variations in instantaneous generation-load mismatch across the continent drive the transmission of renewable surplus to regions with a deficit. Furthermore, the maximum negative values of the mismatch describe the need for dispatchable power capacity, and variations in the mismatch describe the need for on-demand flexible reserves.

Key Metrics

The above considerations give rise to five key metrics that describe a highly renewable electricity system. These are all described formally in Supplemental Information Section 2.3 and summarized here. The first key metric is the average dispatchable electricity. This metric quantifies the amount of energy delivered by dispatchable generators such as biomass, gas, or coal-fired power plants for a fixed wind and solar penetration. It is a good indicator of the utility value of the VREs, i.e., the amount of VRE that can directly cover the demand. This metric was first introduced by Heide et al.[48]

Generally, the useful electricity can be increased by means of geographical dispersion, e.g., by combining national systems to smooth out variations in both demand[49] and renewable generation.[40] We measure this effect with the second metric, which is defined as the absolute difference between balancing electricity required with and without unlimited transmission in a European power grid. We call the metric the absolute benefit of transmission, in contrast to the relative benefit of transmission used by Becker et al.[50] In this paper, we do not detail the required transmission capacities but note that many other studies find that it is cost efficient to build enough to harvest most of this benefit.[50,51] The third key metric provides a measure of the short-term benefit of storage. This key metric is defined as the absolute difference in the dispatchable electricity calculated with and without a 24-h average of the generation-load mismatch. This key metric is presented only for an unlimited transmission scenario, but we stress that a limited transmission scenario introduces no considerable differences for this metric. The reason is that the short-term benefit of storage primarily measures daily smoothing of the generation-load mismatch, whereas the benefit of transmission measures smoothing on the synoptic scale.

The three first metrics are concerned with the need for dispatchable electricity, which is closely related to, e.g., CO_2 emissions, fuel consumption, and VRE curtailment. The fourth and fifth key metrics indicate what is required to stabilize an electricity system based on VREs and to maintain the security of supply. The fourth metric is measured by the maximum dispatchable capacity required during low VRE and high-demand periods. A number of studies show that VRE provides only very limited firm capacity as in Rodriguez et al.[42] However, firm capacity is not a good key metric, as it does not capture the correlation between VREs and demand. The fifth and final key metric is the 3-hourly short-term variability of the balancing time series. This measure was shown to be a good proxy for the need for on-demand reserve capacity.[52] The variability is largely caused by meso-scale turbulence patterns that have been shown to describe the spatio-temporal characteristics of wind and solar power generation well.[53] This means that there is a direct relation between the 3-hourly values used here down to timescales of approximately 10 minutes, where small-scale turbulence changes the scaling.

We note that the effects of many types of extreme weather conditions are implicitly captured by the key metrics that are calculated from the 3-hourly generation-load mismatch. For instance, an extended period of very hot weather in the RCP8.5 scenario would increase the use of dispatchable electricity and capacity as electricity demand for cooling would increase and the performance of solar panels would decrease compared to the historical scenario. Likewise, strong storms would cause wind turbines in areas with wind speeds exceeding, typically, 25 m/s to cut out abruptly, causing an increased short-term variability as well as increased needs for dispatchable electricity and capacity.

DATA AND SOFTWARE AVAILABILITY

Data have been deposited to Mendeley Data and are available at https://doi.org/10.17632/zs55rrrvzw.1.

SUPPLEMENTAL INFORMATION

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AUTHOR CONTRIBUTIONS

Original: G.B.A. developed the original concept, supervised the project, and contributed to the writing. S.K. administrated the project, performed the scientific investigation, wrote the majority of the paper, including the Supplemental Information (apart from Chapter 4), and performed data validation and visualization. H.L. wrote Chapter 4 in the Supplemental Information and provided data on electricity consumption.

Revised: G.B.A. and S.K. contributed equally to the revision and editing processes. S.K. performed all further analysis and visualization of data. H.L. revised Chapter 4 of the Supplemental Information.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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